Does Managed Care Increase Crime?
A Markov Model
of Jail Transitions under Managed Mental Health Care

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Summary

Proposed changes to the mental health care system are usually debated in terms of either health benefits or costs savings. However, because of the extensive intersection between the mental health system and the criminal justice system, changes in the organization and financing of mental health services may change the jail detention rate. We analyze how managed care for Medicaid beneficiaries in King County, Washington (including Seattle), affects jail incarcerations for felonies and non-felonies. We have unique data that tracks individuals in and out of both the public mental health and criminal justice systems for 1993-1998. The final sample size has monthly observations on 42,531 unique individuals aged 18-64. We estimate Markov models of the monthly transition probabilities between living in the community with no public mental health treatment, receiving publicly funded inpatient or outpatient mental health treatment, or being in jail for either a felony or non-felony charge. The transition probabilities are adjusted for demographics and policy changes that occurred during our study period. The one-year probability of jail detention for felonies increased by as much as four percentage points for some subpopulations.

Keywords—mental health; crime; jail; Markov

Introduction

Mental health treatment is expensive. In 1997, Americans spent $73.4 billion on mental health treatment and another $11.9 billion on substance abuse treatment. Expenditures on mental health and substance abuse treatment represent about eight percent of all health care spending. Spending rates in these areas have grown more slowly since 1987 than has overall health care spending (3.7 percent versus 5 percent, controlling for inflation), although spending on psychotropic medication has grown more quickly than spending on pharmaceuticals generally (9.3 percent versus 8.3 percent annual growth) (Coffey et al., 2000).

Both the public and private sectors have responded to rising mental health care expenditures by replacing traditional fee-for-service with managed care for persons with severe mental illness. Mental health carve-outs are one form of insurance that is frequently used to manage mental health care. In a carve-out, the management of claims and sometimes of risk, is separated from the general medical insurance system through a contract with a separate entity or vendor. By 1998, sixteen states had Medicaid waivers to operate a mental health or substance abuse carve-out (GAO, 1999). The carve-out approach is also common among private insurers, with 56 percent of plans reporting use of behavioral health carve-outs (Novartis, 1998). Carve-outs are not the only form of managed care to be used on mental health services. Many of the common tools of managed care used elsewhere are also used for mental health services, including utilization review, prior authorization, and capitated payments. As with other types of managed care, managed care for persons with mental health problems may reduce unnecessary treatment and expenditures. Some managed care contracts may also provide more incentives to encourage prevention, and to maintain medications to avoid hospitalizations.

Managed care critics point out several limitations. Will providers behave in their patients' best interest? Can patients who are denied care negotiate the system to receive services? And, there is concern that managed care will reduce access to needed care, especially for those who may have trouble interacting with health care professionals.

Although the public mental health system is primarily concerned with improving the health of persons with severe mental illness there are a number of additional benefits that spillover to other sectors. Treated persons may be able to live in the community and hold a job. Families may be strengthened. Treated persons may be less likely to engage in substance use. Furthermore, treating persons with severe mental illness may reduce criminal justice detentions for crime—from the petty crimes to more serious offenses. Therefore the effects of managed care, whether good or bad, may affect these other broader social concerns.

Although numerous studies have looked at how managed care for mental health affects access, quality, and cost of care (e.g., Wells et al., 1993; Hodgkin and McGuire, 1994; Sturm et al., 1995; Ellis and McGuire, 1996; Frank and McGuire, 1997; Norton et al., 2002; Lindrooth, Norton, and Dickey, 2002; Domino and Salkever, 2003), few have explored the interaction between managed mental health care and the criminal justice system. Cuellar, Markowitz, and Libby (2003) study youth enrolled in a Colorado state foster care program, and find that the time to jail detention is longer for youth who receive treatment or are in areas with high treatment rates. Scott, Snowden, and Libby (2002) found no significant effect of Medicaid capitation for youth in Colorado who received public mental health services, after controlling for time trends. In a study of adults, Domino and colleagues (2004) find that there was an increase in jail use and costs in King County, Washington after the start of managed care.

In this study we further explore the data from King County, Washington, to investigate whether jail detentions for felonies and non-felonies increased under managed mental health care. We use Markov models to estimate transitions between different states, including living in the community with no treatment, receiving publicly funded care, and being in jail. Because managed care was only implemented for Medicaid beneficiaries, the control group of non-Medicaid beneficiaries controls for contemporaneous time trends. Models are estimated for several sub-populations to test whether the effects of managed care are uniform, or disproportionately affect disadvantaged and minority populations. We find that jail detentions increased for felonies, but not for non-felonies, for several of the subpopulations. The largest effect was on non-white men with SMI, who saw a four percentage point increase in the one-year probability of jail detention for felony charges during the managed care period.

Conceptual Framework

The public's perception of the connection between mental health treatment and crime is perhaps best seen in light of several high-profile cases from Washington State. Starting in the late 1990s there were a string of violent murders by persons with mental illness who had been released from jail or prison. For example, in 1997 Dan Van Ho murdered Stan Stevenson after a Mariners baseball game. Van Ho had a long history of violent behavior and mental illness and was released from jail 11 days prior to the murder, despite warnings from his psychiatrist that Van Ho was dangerous and should be detained (Miletich and Sunde, 1997). Also that year, a convicted sex offender murdered a 52-year old woman soon after being released from prison (George, 1997). These and other murders (sometimes preceded by rape) led to multi-million dollar payouts to the victims' families. As a result, King County, Washington, implemented several policy changes (after the end of our study period) designed to improve public mental health treatment and how the criminal justice system deals with persons with mental health problems. Policymakers responded to the strong perceived connection between public mental health treatment and the prevention of violent behavior.

The scientific evidence of the connection between mental health treatment and crime, however, is more subtle. Recent literature has not found a consistently strong association between having a mental illness and violence, although a greater risk of violent behavior is generally noted when a substance use condition is co-morbid with the mental illness (Swanson et al., 1990; Steadman et al., 1998;). Since these two behavioral health conditions are often linked (US DHHS, 1999), there may in fact be a higher probability of violence among the mentally ill, when substance use is not controlled for in empirical analyses.

The relationship between mental illness and jail detention is even more complex. Individuals come into contact with the criminal justice system when they are charged with a crime, whether or not they will eventually be convicted or not. Jails can be used to hold individuals awaiting court proceedings to determine guilt or innocence, as well as for short-term stays for those convicted. Criminal justice authorities may alter their usual behavior when they encounter symptoms of mental illness, resulting in a different probability of jail detention for any given charge or action (Steadman, 2000). This mediation could go in either direction, increasing or decreasing the likelihood of a jail detention, depending largely on the preferences of the community and the training of the officers or personnel involved. For example, in some communities, officers may receive special training that enables them to better recognize the symptoms of mental illness or they may have access to a trained mental health non-officer specialist; offenders with a mental illness in this community may be more likely to be diverted for treatment rather than being placed under detention at the local jail (Steadman et al., 2000). In other communities, mental health courts may achieve this effect (Steadman et al., 2001). A change in the level of mental health treatments may bring more mentally ill persons to the attention of the criminal justice system, which may result in a change in the rate of jail detentions independent of changes in the actual rate of crime.

Is it plausible that a change to managed care would affect the crime rate? The connection between managed care and actual crime, if any, likely operates through mental health treatment. The effect of managed care on crime should parallel the effect of managed care on mental health status. If managed care improves the effectiveness of mental health treatment and the resulting improved mental health leads to lower levels of incarceration and conviction of mainly minor offenses such as loitering, then crime should decrease. If managed care somehow worsens the effectiveness of mental health treatment or reduces access to treatment and this translates to greater conviction rates, then crime should increase.

Theoretically, either scenario is possible. Advocates of managed care argue that providers have an incentive to provide more preventive care. Opponents of managed care argue that providers have an incentive to cut costs by denying care. The general effect of managed care on crime can only be determined empirically.

What is perhaps more interesting is how the effect of managed care, if any, varies by subpopulation. Studies have shown that women and whites who seek mental health treatment are more likely to engage in treatment than men and blacks (Snowden and Thomas, 2000; Young et al., 2001; Domino and Salkever, 2003). It remains to be seen whether those who are more engaged in treatment are more affected by changes because of greater involvement, or more protected from changes because of knowledge of the system.

We hypothesize that the link between managed care and jail detentions is stronger for non-felony offenses than for felony offices, thus we expect to see a greater change in the probability of being in jail for non-felony offices than for felony offices after managed care. This is because non-felony offenses likely offer more opportunities for discretion by the involved criminal justice officers for jail diversion. The exception might be the rate of drug-related charges, many of which are felony offenses. If under-treated mentally ill individuals are likely to self-medicate with illegal substances, the rate of felony jail detentions may in fact be higher than non-felony offenses.

In summary, the potential link between the under-provision of mental health treatments and the use of the criminal justice system is high. The causal pathway may be direct, with lower treatment receipt leading to higher rates of crime, but also is likely indirect, with more symptomatic individuals more likely to be processed through the jail system.

King County

Our study population, in King County, Washington, allows us the unique opportunity to analyze the effect on jail detentions of a transfer in risk for mental health services from the state to the provider level. Before April 1995, outpatient mental health service providers billed the state on a fee-for-service basis for Medicaid and uninsured individuals. On April 1, 1995, the state put King County at risk for outpatient services and the county responded by shifting the risk to local provider groups through a form of capitated contracts called case-rate payments. Each year, enrollees are assigned to one of several fixed monthly payment amounts depending on their severity of illness. King County also contracted with a private-sector insurer to manage and administer the capitated payment system. We will not be able to identify the separate effects of provider capitation and the Administrative Services Only contract with a private managed behavioral health care vendor that occurred simultaneously, but treat this as one policy change. We refer to this policy change as *managed care*, since the change in structure gave providers the incentive to manage outpatient care.

Data

In order to gather information on persons who ever used either mental health services or jail, we combined information from three different sources: the King County (Washington) jail system, the King County outpatient mental health system, and Washington Medicaid eligibility files. From these three data sources we created a data set of individuals who used at least one of the three systems at some point between July 1993 and December 1998. We obtained service use data for both outpatient treatment and two state psychiatric hospitals, although individuals are not selected for our sample based on their use of the inpatient facility as they are on the outpatient facility. The Medicaid eligibility file provides the information on the period during which a person was enrolled in the Medicaid program during the study period.

The combined data set had information on 42,666 unique individuals, some of whom showed up in all three systems. The data from the jail system included information on 17,801 individuals. During the study period, 22,589 individuals used the King County mental health system, including 1,629 Western State Hospital users. There were 32,565 Medicaid enrollees. The original data set had observations for 66 months per person, for a grand total of 2,815,956 total observations at the person month level. The analytic file was somewhat smaller, however. We excluded elderly persons aged 65 and older and children under age 18 from the analysis. For people who aged into 18 or reached 65 at some point during the study period, we deleted only observations out of the age range. We deleted 202,787 observations due to age restrictions.

We further eliminated some observations during the nine-month transition period between the two time periods; pre-managed care period (21 months: July 1993 through March 1995) and post-managed care period (36 months: January 1996 through December 1998). The nine-month break eliminated 352,248 observations. This allows us to focus on the parameters of interest in steady state rather than a transitional state.

Additional observations were dropped from the analytic file because one state of the world, jail felony, had to be treated as an absorbing state. Most persons convicted of a felony will spend a brief period in jail, and then transfer to state prison. Unfortunately, we do not have access to prison data, and so cannot track how long individuals stay in the criminal justice system before returning to the community. Based on our data alone, we would over-estimate the probability of returning to the community following a jail stay due to a felony. Therefore, in each period we stopped following individuals after they enter jail due to a felony. Jail felony is therefore treated as an absorbing state, which required us to drop 37,112 observations in the pre-managed care period and 109,527 observations in the post-managed care. This will yield unbiased estimates of the transition probabilities. Additional observations were dropped when transforming the data set for the Markov analysis. We created a lagged state variable to obtain states in any two consecutive months, which left up to 55 observations per person (up to 20 in the pre period and up to 35 in the post period). Finally, about one percent of the sample had no Manski-Lerman weights, and were therefore dropped. The final sample had 2,011,204 observations on 42,531 unique individuals.

The analytic longitudinal data set indicates which of four states a person was in each month. States in this study are defined by where an individual is on the first day of each month. Thus, on the first day of a month, people are divided into four mutually exclusive and exhaustive states: live in the community with no public mental health treatment; publicly-funded mental health treatment in either an inpatient or outpatient setting; in jail charged with a felony; and in jail charged with a non-felony. Community is defined as using neither the county mental health system nor the jail system. *Publicly funded mental health treatment* consists of either being in one of the two state psychiatric hospitals, or in an active outpatient treatment episode in the county-funded outpatient mental health system. An active outpatient treatment episode is defined as having at least one visit every six weeks, a somewhat shorter gap then used elsewhere (Huskamp 1999;

Kessler, Steinwachs, and Hanken 1980). During the study period, about 88 percent of the observations were in the community, 12 percent were receiving publicly-funded mental health treatment, and less than a half of a percent were in jail for either a non-felony or a felony (see Tables 1 and 2). It is a limitation of this study that people in any of the states, most likely the community, could be getting private sector mental health treatment.

The change to managed care is a natural experiment. The study design is a pre-post comparison for the treatment group of Medicaid beneficiaries compared to a control group of persons not covered by Medicaid. Therefore, in the empirical methods we estimate difference-in-differences estimators of the effect of managed care on jail detention. Changes in managed care tools should only affect Medicaid enrollees. Medicaid enrollment is defined by whether the person was ever enrolled in Medicaid during the study period (see Table 3). This ever-Medicaid indicator is not endogenous, as a monthly Medicaid indicator might be. Each month, many people enroll and disenroll from the Medicaid program. Some people choose not to enroll until they become sick, making monthly enrollment endogenous with health status. In addition, being in jail may terminate or complicate Medicaid eligibility, thus a time-varying Medicaid enrollment indicator would be endogenous in our model. During the study period, approximately 66 percent of the sample was ever enrolled in Medicaid, and the remaining sample constitutes the control group.

We control for the presence of a serious mental illness (SMI). The SMI variable was created using ICD-9 codes from the three sources of data—the state psychiatric hospital data, the King County outpatient mental health, and the jail system. The specific definition of SMI for this study follows the standard Axis I definition. We define SMI to include schizophrenic disorders (295.xx), affective psychoses (296.xx; except for 296.2 which is a single episode only of major depressive disorder), paranoid states and delusional disorders (297.xx), and other non-organic psychoses (298.xx). The SMI dummy variable equals one if the person was ever diagnosed with one or more types of SMI during the study period. As with the Medicaid variable, the ever-SMI indicator performs better than a monthly SMI indicator. SMI describes a set of long-term chronic conditions. The detection of persons with SMI from administrative data is somewhat problematic, since the incentive for accurate diagnostic codes in many of these systems may not be strong. Thus, we prefer to define SMI status according to whether a person was ever coded as diagnosed as SMI at any point in time. During the study period, about 28 percent of the weighted sample is ever diagnosed as SMI. The sample weights are discussed in the methods section.

We also control for age, sex, and race because these three demographic variables are highly predictive of which state a person will be in. The average age of the sample is 35 and about 45 percent are female (see Table 3). About 70 percent of the weighted sample is white. The remaining 30 percent is predominantly black (16 percent), with small percentages of Asian (5 percent), Native American, Hispanic, other, refugee, and unknown. Because the model needs to be sparse, we only distinguish between white and non-white in our main models.

The most common felonies were related to drug use or possession (43 percent). About 13 percent of felonies were theft, and 11 percent were assault in the first, second, or third degrees. The remaining 33 percent of felonies included a wide variety of offenses, including (in descending frequency) burglary (6.1 percent), forgery (4.7

percent), robbery (3.8 percent), possession of stolen property (2.9 percent), felony violation of court order (2.0 percent), and rape (1.8 percent). Murder and manslaughter combined were less than one percent of felonies. Unfortunately, a large number of detentions could not be classified definitively as either felonies or non-felonies (combine this was robustness discussion). The overwhelming majority of these cases were assaults of unknown degree, theft of unknown degree, and malicious mischief. Non-felony reasons for a jail detention included failure to appear in court, failure to comply with a court order, assault in the fourth degree, driving offenses, and parole and probation violations.

Methods

Markov models have been used in health economics when there are a limited number of states of the world, the states are mutually exclusive and exhaustive, and the researchers are interested in modeling transitions between the different states. In one paper Keeler and colleagues (1987) used Markov models to estimate monthly spending on mental health care using data from the RAND health insurance experiment. In another, Norton (1992) models how prospective payment to nursing homes, along with additional financial incentives to improve quality of care, affects the quality and length of nursing home stay.

There are several reasons why a Markov model is appropriate for the analysis of the King County data. First, we are interested in multiple discrete outcomes. The research questions relate to transitions between several different discrete states, and Markov models are designed to answer such questions. Second, we have censored data for persons who enter jail on a felony charge (because of lack of information on whether they go from jail to prison, and for how long they may stay in prison). Like all duration models, Markov models produce unbiased estimates even with censored data. Third, standard duration models are most appropriate when there is a defined beginning to the period, such as admission to a hospital for a length of stay study; there is no comparable beginning in our data. Fourth, with parameterization, we can control for multiple relevant covariates. Although traditional simple Markov models do not control for covariates, this is one of the technical innovations we apply in this study.

A Markov model is a matrix of probabilities, each element (P_{ij}) of which specifies the probability that a person goes from state *i* to state *j* each period (for a good overview of Markov models, see Kemeny and Snell, 1960). For this study, there are four states: in the community, receiving some publicly funded inpatient or outpatient mental health treatment, in jail on a non-felony charge, and in jail on a felony charge. These four states are mutually exclusive and exhaustive. Therefore, this Markov model is *closed*.

The time period is one month. Therefore, P_{13} indicates the probability that a person currently in the community and not receiving mental health care (state 1) will be detained in jail for a non-felony (state 3) in exactly one month. The choice of period needs to be short enough to pick up most transitions, and long enough so that the off-diagonal elements of the Markov matrix are much greater than zero so that the parameters can be identified. After preliminary investigation, we believe that one month is the appropriate period for the mental health data.

In a linear regression, the way to test for the effect of managed care would be to include dummy variables for the post period, for Medicaid, and their interaction. The sign and significance on the interaction term would indicate the direction and magnitude of the effect of managed care. Our analysis is more complicated. We need to model the transition probabilities as functions of the policy variables in order to test the hypotheses. Therefore, the main independent variables include a dummy variable to indicate the policy change that occurred in King County during the study period, a variable indicating Medicaid eligibility status at any time during our study period, and interactions between the policy change and the Medicaid eligibility. Also, preliminary analysis determined that the probabilities varied greatly by demographic characteristics. Therefore, although many Markov models do not allow the probabilities to be functions of other covariates (e.g., Poterba and Summers, 1986; Keeler, et al., 1987; Norton, 1992), we model each transition probability as a logit function of the policy variables as well as several demographics. The probabilities as a function of the covariates are

$$P_{ij} = \frac{1}{1+e^{-X\beta}} \quad \text{for } i \neq j$$

$$P_{ii} = 1 - \sum_{\substack{i=1 \\ i \neq j}}^{K} P_{ij}$$

where X is a vector of covariates including the constant term, K is the number of states (K = 4 in this study), and β is a vector of parameters to be estimated. All probabilities are constrained to be between zero and one, inclusive.

Although we include covariates in the model, we strive for simplicity. Unlike standard regression models where one additional covariate changes the degrees of freedom by one, in our model the covariate shows up in each cell (except for the diagonal elements), in this case nine times. Adding too many covariates will overfit cells with small probabilities. In a Markov model with no covariates, the number of parameters to be estimated equals the number of initial states times one less than the number of final states. In this case, there are three initial states and four final states, because we treat jail due to felony charge as an absorbing state. Therefore, there are 9 = 3×3 basic parameters. However, because we estimate covariates, the full number of parameters is nine times the number of covariates including the constant term (five), or 80, for each sample.

Most program changes take time to become fully implemented. Therefore, we dropped nine months from April 1995 through December 1995 as a transitional period. Assuming that there is a transitional period, not dropping observations from that time will bias coefficients away from finding an effect.

In addition, we estimated separate Markov models for eight different subpopulations, based on gender, race, and degree of mental health problems. The main purpose of running separate models was to allow the effect of managed care to vary by subpopulation, so that we can test the main hypotheses.

Weights

The data for this study were drawn using choice-based, rather than population-based, sampling. Users of certain system combinations (e.g., jail and county mental health or jail and Medicaid) were oversampled. The choice-based sampling approach requires the use of an appropriate weighting scheme to obtain consistent maximum likelihood estimates (Manski and Lerman, 1977). We modify their approach as suggested by Cosslett (1981), by using information from the sample to generate estimates of the population shares for each time period. The weight for each observation is the ratio of the population share of each choice to the sample share. Choice is defined as one of eight possible combinations of the three service systems (jail, county mental health, and Medicaid). The weights are calculated each period. The number of observations in jail is much smaller in the weighted data than in the original sample because of the oversampling (see Table 1). All numbers in Tables 2 and following are based on the weighted data.

Although calculating the sample share for each choice is straightforward, we did not have information on the population share in each time period, but only had access to a weighting system for the population of persons who had ever used any of the service systems during the study period. We obtained an estimate of the number of persons in each system category by combining information about the probability of each choice each time period and the U.S. Census annual estimates of the population (for details, see Domino et al., 2004 forthcoming).

The likelihood function is a product of probabilities, with one term for each observed transition. The log likelihood function is the sum of the logarithm of the probabilities over all observations from 1 to *N*, weighted by their Manski-Lerman weights w_n.

$$\ln(L) = \sum_{n=1}^{N} w_n \ln\left(P_{i_n j_n}\right)$$

Simulations

The estimated Markov probabilities do not, on their own, answer the research questions about the magnitude or statistical significance of the effect of managed care on the probability of jail detentions. To do that requires running simulations, because in nonlinear models the magnitude and statistical significance of interaction terms cannot be determined by the coefficient on the interaction term alone (Ai and Norton, 2003). Because we have a pre-post treatment-control experiment, with the policy of managed care implemented in April of 1995 and Medicaid being the treatment group, we can simulate probabilities of entering jail for each combination of pre-post and treatment control. The effect of managed care is the difference-in-differences estimator

[Pr(jail|post, Medicaid) – Pr(jail|pre, Medicaid)] –

[Pr(jail|post, non-Medicaid) – Pr(jail|pre, non-Medicaid)]

Therefore, we simulate the probability of entering jail (for either a felony or a non-felony) four times for each of the eight subpopulations.

We test the hypotheses by looking at the difference-in-differences estimator for the probabilities of being in the four states at the end of one year. The simulations are done for a sample of 10,000 people age 20. We vary the gender, race, mental health status, and age for eight subpopulations. For these simulations, we start all persons in the community. For these simulations, jail is an absorbing state. The reason for this is to see if the probability of being in jail, for either a felony or a non-felony, changes after the introduction of managed care. Standard errors will be computed by bootstrapping.

Robustness checks

We will test the robustness of our results to several changes in specification or definition of variables. First, the definition of felony is not always clear in the data. For example, assaults of the first, second, and third degree are felonies but an assault in the fourth degree is a misdemeanor (non-felony). Therefore, if the data lists assault as the reason for jail detention, but does not list the degree, it was not possible to know for sure if it was a felony or a non-felony. We ended with three categories of offenses: definite felonies, possible felonies, and non-felonies. Our main results define felonies as definite felonies only. To test the robustness of our results we will run the models with possible felonies combined with definite felonies, then combined with non-felonies.

Nearly one-half of the observations in the weighted sample that are non-white are also non-black. If we were running a single regression, then adding variables for the multiple other racial categories would be preferred. However, because each additional covariate uses up many degrees of freedom, it is not possible to have a fully saturated model. To test the robustness of our results we will try different specifications of the racial variables.

There is another possible kind of weight we could employ other than our current weights which are based on Manski and Lerman (1977). The Manski-Lerman weights will let us get back to the actual King County, Washington, population. However, unadjusted sampling weights should give estimates based on the population who show up at least once in three administrative data sets; that is, the population of individuals with some contact with either the Medicaid, county mental health or jail system during our 5.5 year study period. The difference in weights is not large, but the inference one makes is different and important. We prefer to use the Manski-Lerman weights because we think that the general population is preferable to a conditional one, but we also want to make sure that the results are not driven by small differences in weighting. To test the robustness of our results, we will estimate the model with unadjusted sampling weights.

The length of the transition period (assumed to be nine months) is arbitrary, so is subject to a sensitivity test. Dropping too many months will lead to a loss in precision, but should not affect the bias. To test the robustness of the nine-month assumption of a transitional period, we will try both shorter and longer periods.

The Markov model estimates one-month transition probabilities. We have complete data on where a person is on each day (except for lack of information on prison terms and movement out of King County). We arbitrarily chose the first day of the month to define where someone is. In some types of data, there are strong effects of time of the month. For example, because most employees are paid either monthly or semi-monthly, there are strong monthly effects on the financial markets. We are not aware of any reason why transitional probabilities should be a function of day of the month, but to test this, we will re-compute where everyone was on different days of the months, and re-run all the models. We will try the 10^{th} and 20^{th} day of the month.

Results

The maximum likelihood Markov model results confirm that for most cells, there are significant differences between pre and post, and between Medicaid and non-Medicaid. Although we estimated results for all eight sub-samples, in addition to the entire sample, the results are only shown for one representative group (see Table 4) because the results are hard to interpret on their own, and there are so many parameters estimated. The results in Table 4 are for nonwhite men with SMI. In all models the coefficients for post, Medicaid, the interaction of post and Medicaid, and age are significant in most cells, especially ones in which the sample sizes are not small. The coefficients on the interaction terms for post period and Medicaid for cells going to jail are generally positive and statistically significant. The probability of going to jail generally declines with age. Although many of the coefficients are statistically significant, it remains to be seen in the simulation whether the magnitudes are economically significant.

Simulations

The simulations show the percentage point change in the probability of ending up in each of the four states due to managed care. The results are shown separately for each Markov model, meaning for each combination of gender, race, and mental health status. The effect of managed care may differ for each subpopulation, equivalent to fully interacting the models. The simulations fix age at 20 years old. Like the MLE Markov models, jail detention due to a felony is treated as an absorbing state. Therefore, the simulations compute the cumulative probability of a jail detention due to a felony. In contrast, for jail non-felony the simulations compute the probability of being in jail after exactly one year due to a non-felony. The difference between cumulative and non-cumulative probabilities makes the interpretation challenging.

Managed care greatly increases the probability of a jail detention due to a felony for non-white men with SMI (see Table 6A). The increase is nearly four percentage points, off of a base probability of about ten percent. There is a compensating decline in the probability of being in the community. The probabilities of being in public mental health or jail non-felony are nearly unchanged. The group with the second largest change was white men with SMI (see Table 6B). For them the probability of jail detention due to a felony increased by more than two percentage points, off of a base percentage of about five percent. There were two other groups that had an increase in jail felonies of more than one percentage point, off of a base percentage of between four and six percent. These groups were nonwhite females with no SMI (see Table 6C), and white males with no SMI (see Table 6D). For all groups, the difference-in-differences estimators for the changes in public mental health and jail non-felony were less than one percentage point.

We also tried estimating the models with both jail felony and jail non-felony as absorbing states, and the results were broadly similar. The magnitude of the effect of managed care was positive and several percentage points for the subsamples of men with SMI (both white and nonwhite).

Before saying whether these differences are statistically significant, we need to bootstrap the standard errors. However, we can say that the magnitudes are economically significant.

Conclusion

There are three main policy results. First, although researchers usually focus on the direct effects of managed mental health care, or other changes in mental health policy, this study shows that there are consequences that spill over into the criminal justice system. The jail detention rate increased for felonies following the introduction of managed care. Our difference-in-difference results control for baseline differences between the Medicaid and non-Medicaid populations, and for general time trends in incarceration rates. The magnitudes of the effects are quite large—as much as a four-percentage point increase in felony jail detentions.

Second, the increases found in jail detentions across several subpopulations were always for felonies, never for non-felonies. We had anticipated that managed care might have a stronger effect on non-felonies, but that was not supported by the data. This may be due to the high prevalence of drug related felonies. We will examine felonies by subcategory in future analyses. This result implies that the total societal costs of managed care are much larger than one would find by ignoring this spillover effect.

Third, the results are not uniform for all subpopulations. The effects of managed care are strongest for men with SMI (both white and non-white). However, this effect appears to be greatest for male persons of color. This might suggest that the implementation of a managed behavioral health care carve-out has an additive effect with long-recognized institutional biases toward the incarceration of people of color. This is an area for future research. They are moderate for white men without SMI and non-white women with SMI. The other four subgroups seemed to be unaffected by managed care.

There are three methodological results of note. First, Markov models are useful for modeling how people move between the community, public mental health treatment, and jail. Markov models are relatively rare in the health economics literature, but for certain applications they are quite appropriate. Second, unlike most other studies that estimate Markov models, we estimate the transition probabilities as functions of covariates. This is an innovation that is important for testing hypotheses on subpopulations. Third, the use of difference-in-differences estimators to test the hypotheses in simulations is unique.

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Table 1. Transition matrices of counts (both weighted and unweighted) for entire study period.

This Month	Next Month				
			Jail		
	Community	Public MH	Non-Felony	Felony	Total
Unweighted					
Community	1,727,446	21,761	5,220	7,333	1,761,760
Public MH	18,537	220,517	410	1,172	240,636
Jail Non-felony	5,169	451	2,953	235	8,808
Total	1,751,152	242,729	8,583	8,740	2,011,204
Weighted					
Community	2,006,170	2,301	1,209	4,634	2,014,314
Public MH	7,902	28,155	28	130	36,215
Jail Non-felony	5,430	72	683	47	6,323
Total	2,019,502	30,528	1,920	4,811	2,056,852

Weights were computed using the Manski-Lerman (1977) method.

Table 2. Transition matrices of probabilities (weighted) for entire study period, and for the pre and post periods.

This Month	Next Month: Community	Public MH	Jail: Non-felony	Jail: Felony
Entire study period				
Community	99.60	.11	.06	.23
Public MH	21.82	77.74	.08	.36
Jail Non-felony	85.88	1.14	10.80	.74
Pre period (21 months)				
Community	99.52	.015	.063	.26
Public MH	33.26	66.31	.055	.37
Jail non-felony	87.35	.71	11.25	.70
Post period (35 months)				
Community	99.64	.092	.058	.21
Public MH	14.60	84.96	.093	.35
Jail non-felony	87.02	1.39	10.81	.78

The probabilities were computed from Table 1 by dividing each count by the row total. Weights were computed using the Manski-Lerman (1977) method.

Table 3. Summary statistics for entire weighted sample (N = 2,056,852).

Variables	Mean	Standard Deviation	Minimum	Maximum
Policy Variables				
Managed care	.643	.479	0	1
Medicaid	.66	.474	0	1
Managed care ×Medicaid	.419	.493	0	1
Demographics				
Age	34.9	10.5	18	64
Female	.449	.497	0	1
SMI	.279	.448	0	1
Nonwhite	.303	.460	0	1

Weights were computed using the Manski-Lerman (1977) method.

Table 4. Maximum Likelihood Estimator results for the Markov model, controlling for covariates, for a representative group (male, nonwhite, and SMI).

	Next Month			
			Jail	
This Month	Community	Public MH	Non-Felony	Felony
Community				
Constant		−7.73***	−6.79***	−4.79***
		(.19)	(.2077)	(.15)
Post		−.65***	.28	−.64***
		(.24)	(.43)	(.20)
Medicaid		.24	.55	.052
		(.20)	(.40)	(.17)
Post × Medicaid		.40	−.23	.65***
		(.28)	(.49)	(.23)
Age−20		.0088	−.025**	−.031***
		(.0063)	(.011)	(.0057)
Public Mental Health				
Constant	−.28**		−6.56***	−3.51***
	(.12)		(1.44)	(.44)
Post	−1.017***		−.98	−1.023*
	(.13)		(1.96)	(.56)
Medicaid	−.83***		−.28	−.97**
	(.12)		(1.36)	(.48)
Post × Medicaid	.28*		.30	.903
	(.17)		(2.19)	(.71)
Age−20	−.0143***		−.00010	−.028
	(.0025)		(.046)	(.018)
Jail Non-Felony				
Constant		−4.45***	−1.90***	−3.55***
		(1.46)	(.3209)	(.97)
Post		.22	−.15	−.5392
		(1.55)	(.55)	(.6689)
Medicaid		.35	−.31	−.41
		(1.54)	(.56)	(1.066)
Post × Medicaid		.23	−.23	.72
		(1.74)	(.68)	(1.28)
Age−20		.016	.0057	.020
		(.036)	(.017)	(.031)

* p < .1 ** p < .05 *** p < .01

Table 5. Estimated Markov transition matrix for 20-year old nonwhite male with SMI in the post period on Medicaid.

	Next Month			
			Jail	
This Month	Community	Public MH	Non-felony	Felony
Community	.9860	.0032	.0021	.0088
Public MH	.1363	.8528	.0010	.0099
Jail Non-felony	.8411	.0255	.1060	.0274

Table 6A. One-year simulated probabilities with Jail Felony as an absorbing state on 20-year-old nonwhite males with SMI. *(Male & Nonwhite & SMI subgroup)*

			Jail	
	Community	Public MH	Non-felony	Felony
Post, Medicaid	.9016	.0027	.0009	.0948
Pre, Medicaid	.9452	.0020	.0012	.0516
Post, Non-Medicaid	.8924	.0035	.0017	.1024
Pre, Non-Medicaid	.8973	.0025	.0019	.0983
Difference-in-differences	−.0387	−.0003	−.0001	.0391

Table 6B. One-year simulated probabilities with Jail Felony as an absorbing state on 20-year-old white males with SMI. *(Male & White & SMI subgroup)*

			Jail	
	Community	Public MH	Non-felony	Felony
Post, Medicaid	.9363	.0020	.0018	.0599
Pre, Medicaid	.9400	.0022	.0010	.0568
Post, Non-Medicaid	.9644	.0014	.0007	.0335
Pre, Non-Medicaid	.9466	.0019	.0010	.0505
Difference-in-differences	−.0215	.0003	.0011	.0201

Table 6C. One-year simulated probabilities with Jail Felony as an absorbing state on 20-year-old nonwhite males without SMI. *(Male & Nonwhite & noSMI subgroup)*

			Jail	
	Community	Public MH	Non-felony	Felony
Post, Medicaid	.9263	.0001	.0016	.0720
Pre, Medicaid	.9074	.0000	.0014	.0912
Post, Non-Medicaid	.9184	.0002	.0008	.0806
Pre, Non-Medicaid	.9020	.0002	.0014	.0964
Difference-in-differences	.0025	.0001	.0008	−.0030

Table 6D. One-year simulated probabilities with Jail Felony as an absorbing state on 20-year-old white males without SMI. *(Male & White & noSMI subgroup)*

			Jail	
	Community	Public MH	Non-felony	Felony
Post, Medicaid	.9535	.0000	.0009	.0456
Pre, Medicaid	.9554	.0002	.0013	.0431
Post, Non-Medicaid	.9517	.0002	.0006	.0475
Pre, Non-Medicaid	.9404	.0004	.0008	.0584
Difference-in-differences	−.0132	.0000	−.0002	.0134

Table 6E. One-year simulated probabilities with Jail Felony as an absorbing state on 20-year-old nonwhite females with SMI. *(Female & Nonwhite & SMI subgroup)*

			Jail	
	Community	Public MH	Non-felony	Felony
Post, Medicaid	.9509	.0036	.0017	.0438
Pre, Medicaid	.9478	.0030	.0003	.0489
Post, Non-Medicaid	.9722	.0011	.0009	.0258
Pre, Non-Medicaid	.9725	.0041	.0005	.0229
Difference-in-differences	.0034	.0036	.0010	−.0080

Table 6F. One-year simulated probabilities with Jail Felony as an absorbing state on 20-year-old white females with SMI. *(Female & white & SMI subgroup)*

			Jail	
	Community	Public MH	Non-felony	Felony
Post, Medicaid	.9557	.0031	.0009	.0403
Pre, Medicaid	.9625	.0041	.0010	.0324
Post, Non-Medicaid	.9786	.0016	.0003	.0195
Pre, Non-Medicaid	.9852	.0020	.0003	.0125
Difference-in-differences	−.0002	−.0006	−.0001	.0009

Table 6G. One-year simulated probabilities with Jail Felony as an absorbing state on 20-year-old nonwhite females with NoSMI. *(Female & Nonwhite & NoSMI subgroup)*

			Jail	
	Community	Public MH	Non-felony	Felony
Post, Medicaid	.9857	.0001	.0002	.0140
Pre, Medicaid	.9784	.0002	.0002	.0212
Post, Non-Medicaid	.9788	.0002	.0000	.0210
Pre, Non-Medicaid	.9586	.0011	.0002	.0401
Difference-in-differences	−.0129	.0008	.0002	.0119

Table 6H. One-year simulated probabilities with Jail Felony as an absorbing state on 20-year-old white females without SMI. *(Female & White & NoSMI subgroup)*

			Jail	
	Community	Public MH	Non-felony	Felony
Post, Medicaid	.9863	.0002	.0002	.0133
Pre, Medicaid	.9900	.0003	.0005	.0092
Post, Non-Medicaid	.9692	.0000	.0003	.0305
Pre, Non-Medicaid	.9810	.0009	.0002	.0179
Difference-in-differences	.0081	.0008	−.0004	−.0085